Biodiversity

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This RFI-2 submission focuses primarily on Theme III "Marine and Terrestrial Ecosystems and Natural Resource Management".

Q1 - Importance: Human activities are causing rapid changes in biodiversity across the globe. These changes are often irreversible and have major ramifications for the broader Earth system and human well-being. There is an urgent need for an integrated global observing system designed to quantify biodiversity on Earth and detect change through time. Such a system, supported by satellite remote sensing providing regularly repeated, systematic biodiversity data with global coverage and high spatial resolution, could profoundly deepen our understanding of the pace and consequences of biodiversity change, and transform our ability to predict and manage the future of Earth's life support systems [1–9].

A global biodiversity observing system could address the following science and application objectives: *(O1) Characterize the global patterns of biodiversity with significantly higher spatial resolution and coverage than currently available. (O2) Determine how biodiversity is changing globally at landscape and regional scales and attribute those changes to specific drivers. (O3) Determine how biodiversity changes influence key ecosystem functions (e.g., productivity) at regional to global scales. (O4) Improve predictions of the future likelihood and potential consequences of biodiversity change with an emphasis on identifying critical tipping points in Earth's life support systems.*

Biodiversity, short for biological diversity, is the variety of life on Earth. It includes the variation among genes, species, their functional traits, the ecosystems within which they live, and how they interact (Figs. 1 & 2). This complex web of life forms drives the functioning of ecosystems through countless reciprocal interactions among organisms and the abiotic environment. These maintain the processes (e.g., productivity, evapotranspiration, and decomposition) that control the fluxes of carbon, water, nutrients, and energy through the Earth system. Human well-being depends on biodiversity as a consequences of the ecosystem services it renders[10,11]; human societies rely upon and benefit from the goods (like food, wood, and medicines), environmental regulating services (like erosion control or climate regulation through carbon sequestration and water cycling), and countless aesthetic and cultural services that biodiversity provides.

Despite its vital importance, Earth's biodiversity is experiencing rapid and widespread decline and alterations due to multiple interacting anthropogenic drivers[12]. These include the loss, degradation, and fragmentation of natural habitats, climate change, the spread of invasive species and diseases through global trade and travel, overexploitation (the unsustainable removal of organisms, e.g. overfishing), and pollution especially ocean acidification and the build-up of nutrients from fertilizers. Despite accelerating policy and management responses, many of these anthropogenic drivers of biodiversity loss continue to worsen[13].

Current rates of species extinction are now ~100 times higher than background rates in the long-term fossil record[14] (Fig. 3). This rate is unprecedented in human history and may be comparable to the five mass extinctions in Earth's history (Barnosky et al. 2011); the most recent one saw the disappearance of the dinosaurs sixty-five million years ago. An index of species populations of many vertebrate animals, keystone indicators of overall biospheric integrity, shows a 52 percent decline over the last 40 years[15] (Fig. 4). Although biodiversity is declining globally, at local scales ecosystems are not systematically losing species[16], but rather are experiencing rapid shifts in species composition and abundance (turnover); sometimes resulting

in communities with entirely novel species configurations [17] with unknown consequences [18]. The rapid pace of both biodiversity loss and change necessitates urgent action to develop a baseline map of the global patterns of biodiversity (O1) at much finer spatial grains than currently available and if possible at species level[4,19]. It is critical to know the current status of biodiversity in order to know how it is changing and why (O2).

Mounting evidence synthesized from many biodiversity manipulation experiments, conducted primarily at the field and lab scale, indicate that biodiversity changes threaten the ecosystem services essential for human well-being[20–25]. Consensus findings [23] show that biodiversity loss tends to degrade ecosystem functioning (Fig. 5) and increase ecosystem vulnerability to environmental change (i.e. decrease ecosystem resilience). Many experiments show that influence of biodiversity loss on ecosystem functioning is often comparable to direct influence of other anthropogenic pressures[26,27]. Further analyses of multiple experiments reveal that these biodiversity effects increase over time[28], with increased spatial scale [29], and when multiple functions are considered simultaneously[30,31].

However, at regional and global scales[32,33], relatively little is known quantitatively about how much and what kinds of biodiversity can be lost before key aspects of ecosystem functioning are eroded (O3). The extent and rate at which biodiversity losses are pushing ecosystems towards critical tipping points in to undesirable and irreversibly degraded states with decreased functioning and dangerous reductions to ecosystem services remains a major gap in Earth system knowledge[34–37] (O4; Fig. 6).

Q2 - Utility: Global observations of multiple components of biodiversity and drivers of biodiversity change are needed to tackle the urgent global biodiversity crisis and to address the four science objectives listed above. New satellite observing technologies, currently available but not yet deployed at scale, integrated with *in situ* measurements will enable transformative progress.

Basic biodiversity science and applied conservation efforts have been slowed by the scarcity and quality of available biodiversity data[19,38]. Currently available global data on biodiversity are grossly incomplete and non-representative taxonomically, geographically, environmentally, temporally, and functionally. While datasets of species traits and their connection to function continue to grow[39,40], local observations of species traits remain highly insufficient. For example, on average only around 2% of vascular plant species have any trait measurements available at the regional scale and an even smaller proportion in the species-rich tropical regions[8] (Fig. 7). Data on other biodiversity attributes such as species occurrence, abundance, and biomass hold similar biases[6,41].

These data gaps and biases are exacerbated by even scarcer information on temporal changes in biodiversity. Even in areas in which current data are relatively complete, widespread biodiversity change driven by anthropogenic pressures is rapidly outpacing incremental gains afforded by laborious *in situ* biodiversity sampling[4]. Furthermore, existing "global" data has not been collected consistently or systematically, but is instead compiled post hoc from thousands of

disparate research activities, often not designed to address long-term trends or large-scale patterns[42].

As a response to these challenges, the Group on Earth Observations Biodiversity Observation Network (GEO BON) has proposed a candidate set of Essential Biodiversity Variables[3] (EBVs; Fig. 8) – grouped broadly into species traits and populations, ecosystem structure and function, and genetic and community composition. These EBVs are modeled after the fifty Essential Climate Variables[43] (ECVs) that guide the implementation of the Global Climate Observing System (GCOS), which supports the work of the United Nations Framework Convention of Climate Change and the Intergovernmental Panel on Climate Change (IPCC). Similarly, the goal of the proposed EBVs is to support the equivalent body to the IPCC for biodiversity, the recently-established Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services[44] (IPBES) and several multilateral international environmental agreements, most notably enabling progress towards the Aichi Biodiversity Targets[45] set by the international community through the Convention on Biological Diversity (CBD).

Space-observable EBVs have been identified by multiple working groups[5,7–9,46]. Space agencies have coordinated for decades through the Committee on Earth Observation (CEOS) to produce the Climate Data Records from which ECVs are derived. **The biodiversity community is now strongly urging the GEO secretariat to support the definition of a final set of agreed upon space-observable EBVs and for space agencies to coordinate through CEOS to develop the missions and data products necessary to monitor EBVs[7].**

Some of these space-observable EBVs will overlap directly with ECVs, (e.g. Leaf Area Index), and some are already being monitored from space[9]. Other EBVs could be measured from space (or inferred from space-based measurements with additional modeling and/or in situ data) in the near future with advanced observing technologies that are mature and available but not yet deployed at scale. For example, ecosystem structure and aboveground vegetation biomass will soon be measured globally using space-based lidar (GEDI) and radar observations (NISAR). Further discussion of these biodiversity targets can be found in RFI-2 response *3D Vegetation Structure and Dynamics* (Lavalle et al). Other RFI-2 responses addressing biodiversity science targets include *Monitoring Coastal and Wetland Biodiversity from Space* (Muller-Karger et al.)*, Global Terrestrial Ecosystem Functioning and Biogeochemical Processes* (Townsend et al.)*, Ocean Ecosystems (*Behrenfeld et al.), and *Coral Reefs: Living on the Edge* (Hochberg et al.).

For the remainder of this RFI response, we will focus on the utility, key requirements, and affordability of measuring the functional diversity of terrestrial plants, one of many Essential Biodiversity Variables. Jetz et al.[8] have recently identified global spaceborne measurements on the functional composition and diversity of plant communities (O1) as an essential foundation (Fig. 9) for monitoring biodiversity change (O2), understanding the functioning of ecosystems (O3), and predicting and managing the consequences of future biodiversity change (O4).

Plant functional biodiversity encompasses the wide-ranging variation in physiological, morphological and chemical properties (known in the ecological literature as functional traits) of

plants. These include the concentration of metabolites and nonstructural carbohydrates in leaves, or the ratio of leaf mass to area, which are related functionally to plant processes like carbon and water uptake, nutrient cycling, and defense against pests and environmental stresses (see Table 1 for a list of functional traits observable from space). These functional properties vary within and among individuals (e.g., based on the position of a leaf on a plant and its exposure to sunlight, or the variability among trees in a forest) to populations, species, and communities, and may be measured at any of these levels of biological organization[47].

With increasing spatial scale (i.e. coarser spatial resolution of measurement), the retrieval of functional properties will increasingly represent the aggregate properties of many individuals and species, including, for example the functional biodiversity of whole plant communities. Such aggregate "functional diversity" metrics characterizing the breadth of functional properties of a group of organisms are known to be strongly associated with taxonomic[48,49] and phylogenetic[50,51] measures of biodiversity and their potential decrease under habitat loss[52]. Plant functional traits are strongly associated with the distribution and abundances of animals[53–58] (Fig. 10), fungi[59], and soil microbes[60,61]. Finally, the close links between plant functional biodiversity and ecosystem processes such as carbon, water and energy exchange enabling a more mechanistically detailed and predictive representation of the terrestrial biosphere in Earth system models[62–64].

Q3- Requirements: We understand the key requirements for observing the diversity of terrestrial plant functional traits from space based on mature algorithms developed from airborne studies conducted across multiple biomes[65–67] (Fig 11).

The the **underlying physical observable** for retrieving plant functional traits from space are atmospherically corrected surface reflectances covering 450-2450 nm with <=10 nm **spectral resolution**. This is the the **spectral range** that is sensitive to key plant chemical, physiological, and leaf to canopy light-scattering characteristics. Specific portions of the spectrum are also required for atmospheric correction. The visible portion of the spectrum 450 to 700 nm and the oxygen A-band centered at 760 ±20 nm are required for aerosol estimation. Water vapor information is derived from the two water absorptions at 940 ±80 nm and 1150 ±100 nm. Cirrus cloud assessment and correction information is derived from the strong water bands between 1380 ±20 nm and 1875 ±30 nm.

Radiometric performance requirements (0 to max vegetated surface signal, $\geq$ 90% accuracy, and $\geq$ specified SNR) are driven by the **range of radiances and required SNR** necessary to retrieve the physical trait parameters with sufficient precision and accuracy to meet or exceed ecosystem model sensitivity and atmospheric correction requirements with demonstrated retrievals from airborne imaging spectrometer measurements with known SNR performance. To bracket the range of ecosystems observed, at-sensor radiance has been modeled for an upper-mid latitude conifer and tropical broadleaf canopy (Fig. 12). Identification of narrowband features associated with leaf absorption features requires SNR commensurate with the depth of spectral features (Fig. 12). **Geometric requirements** include ±90 m surface location to ensure alignment with global DEM data for correction of illumination and bidirectional reflectance effects.

The **spatial resolution** requirement is ≤40 m in order to capture individual stands (groups of trees of a common species) within forest ecosystems and maximize the diversity observed while allowing global coverage. Spatial sampling requirements are derived based on ecosystem scale analyses and spatial tests of sequentially degraded aircraft data collected at 1–5 m. Multi-scaled analyses [68] show that large-scale plant trait variability is well resolved with 20–40 m^2 data, capturing the natural variability in vegetation across landscapes while minimizing intra-canopy effects (i.e., the pixel is a canopy, not part of a canopy).

The baseline **spatial coverage and temporal frequency** requirement is at least one cloud-free measurement in the peak growing season for ≥90% of the Earth's vegetated terrestrial surface per year. Cloud-free views allow retrieval of the full set of surface spectral reflectance. The **baseline observation duration** requirement is driven by the need to detect changes in the retrieved trait parameters to track changes in biodiversity over time.

Q4 - Affordability: The measurements can be achieved affordably in the decadal timeframe, due to investments in response to global terrestrial/coastal coverage missions outlined in the 2007 NRC Decadal Survey[69] and NRC Landsat and Beyond report[70] and other initiatives. These measurements would build on a legacy of airborne and space instruments including airborne: AIS[71], AVIRIS[72], and AVIRIS-NG[73] and space: NIMS[74], VIMS[75], Deep Impact[76], CRISM[77], EO-1 Hyperion[78,79], M3[80] and MISE, the imaging spectrometer now being developed for NASA's Europa mission.

NASA-guided engineering studies in 2014 and 2015 show that a Landsat-class VSWIR (380 to 2510 nm @ ≤10 nm sampling) (Fig. 13) imaging spectrometer instrument with a 185 km swath, 30 m spatial sampling and 16 day revisit with high signal-to-noise ratio and the required spectroscopic uniformity can be implemented affordably for a three year mission with mass (98 kg), power (112 W), and volume compatible with a Pegasus class launch or ride-share (Fig. 14). Cloud probability analysis completed using the MODIS Terra and Aqua cloud products following Mercury et al.[81] shows shows the baseline spatial coverage and temporal frequency measurement requirements can be met.

The key for this measurement is an optically fast spectrometer providing high SNR and a design that can accommodate the full spectral and spatial ranges[82]. A scalable prototype F/1.8 full VSWIR spectrometer [83] has been developed, aligned, and is being qualified (Fig. 15).

Data rate and volume challenges have been addressed by development and testing of a lossless compression algorithm for spectral measurements[84–86]. This algorithm is now a CCSDS standard. With compression and the current Ka band downlink offered by KSAT and others, all terrestrial/coastal measurements can be downlinked (Fig. 16).

Algorithms for calibration[72] and atmospheric correction[87–89] of large diverse data sets have been benchmarked as part of the HyspIRI preparatory campaign[90] as well as for the AVIRIS-NG India and Greenland campaigns and elsewhere. **The data algorithms necessary for achieving the required plant trait measurements are mature and have been tested over large diverse datasets (summarized in Table 2).** To enhance affordability and accelerate measurement

availability, there is good potential for international partnerships.

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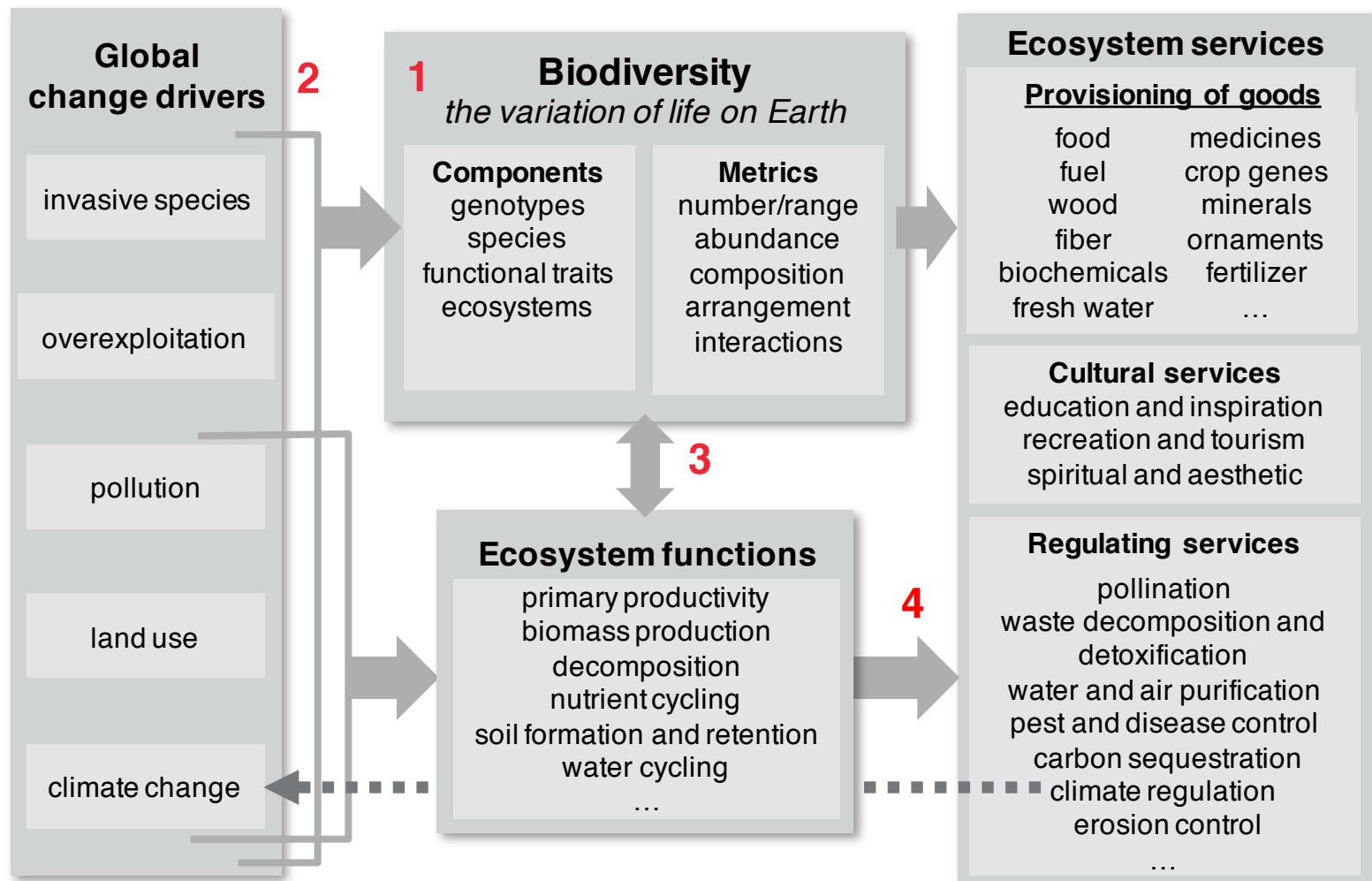
Figure 1: Human activities are driving rapid changes in global biodiversity with profound effects on ecosystem functioning and the ecosystem services on which human society relies. In the biodiversity box, the components of biodiversity (genotypes, species, functional traits, and ecosystems) can each be measured in multiple ways (number/range, abundance, composition, spatial arrangement, and the interactions between biological units) as explained in Fig 2. The red numbers correspond to our four science objectives. Adapted from Díaz et al (2006) and Millennium Ecosystem Assessment (2005).
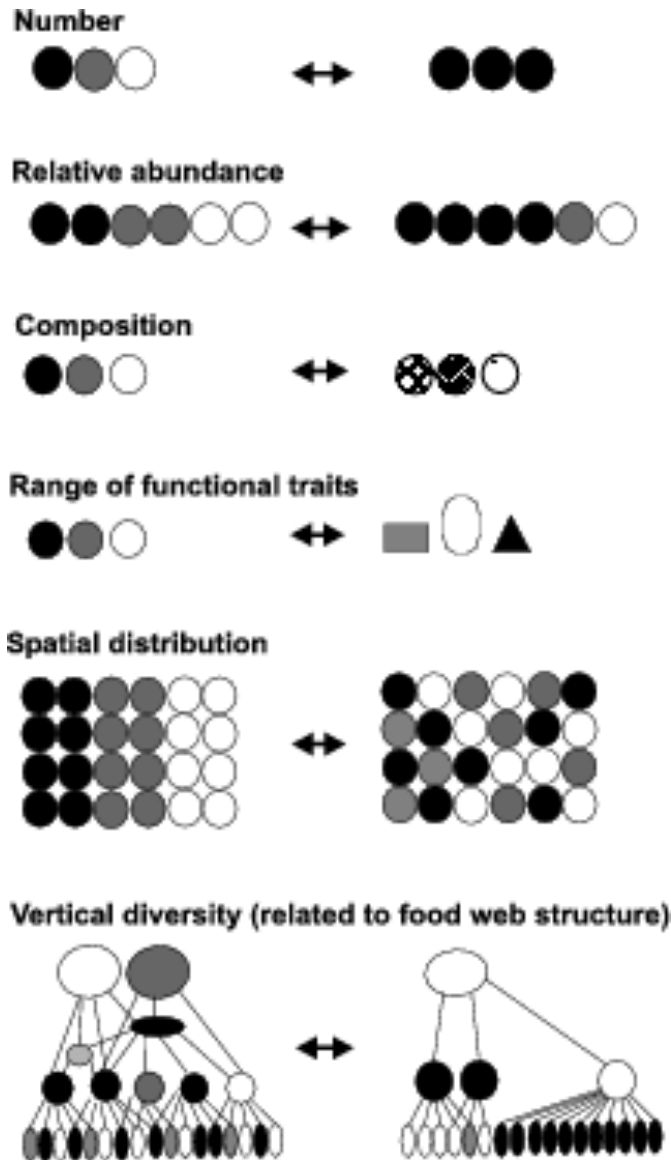
Figure 2: The Different Metrics of Biodiversity.

All of these biodiversity metrics can be affected by human intervention (arrows), and in turn have repercussions for ecosystem properties and services. Symbols represent individuals or biological units. Symbols of different shades represent different genotypes, species, functional traits, or ecosystems.

Image from Díaz et al (2006).
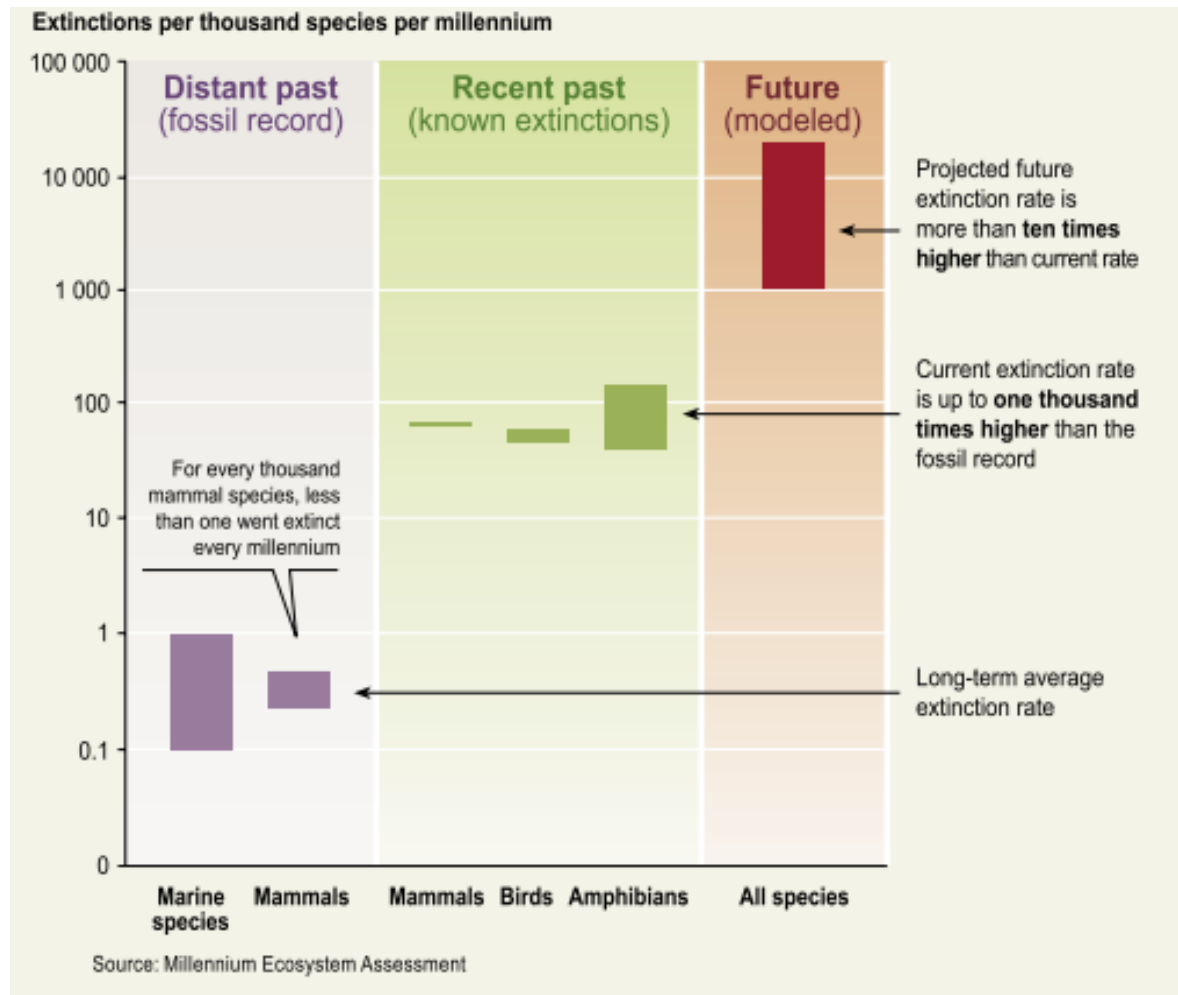
Figure 3: Current extinction rates are ~100 times higher than the long-term fossil record and projected to increase in the future. These rates could be severe enough to match the extinction magnitudes of the five mass extinctions from Earth's deep past in as little as three centuries (Barnosky et al. 2011) Image from the Millennium Ecosystem Assessment (2005).
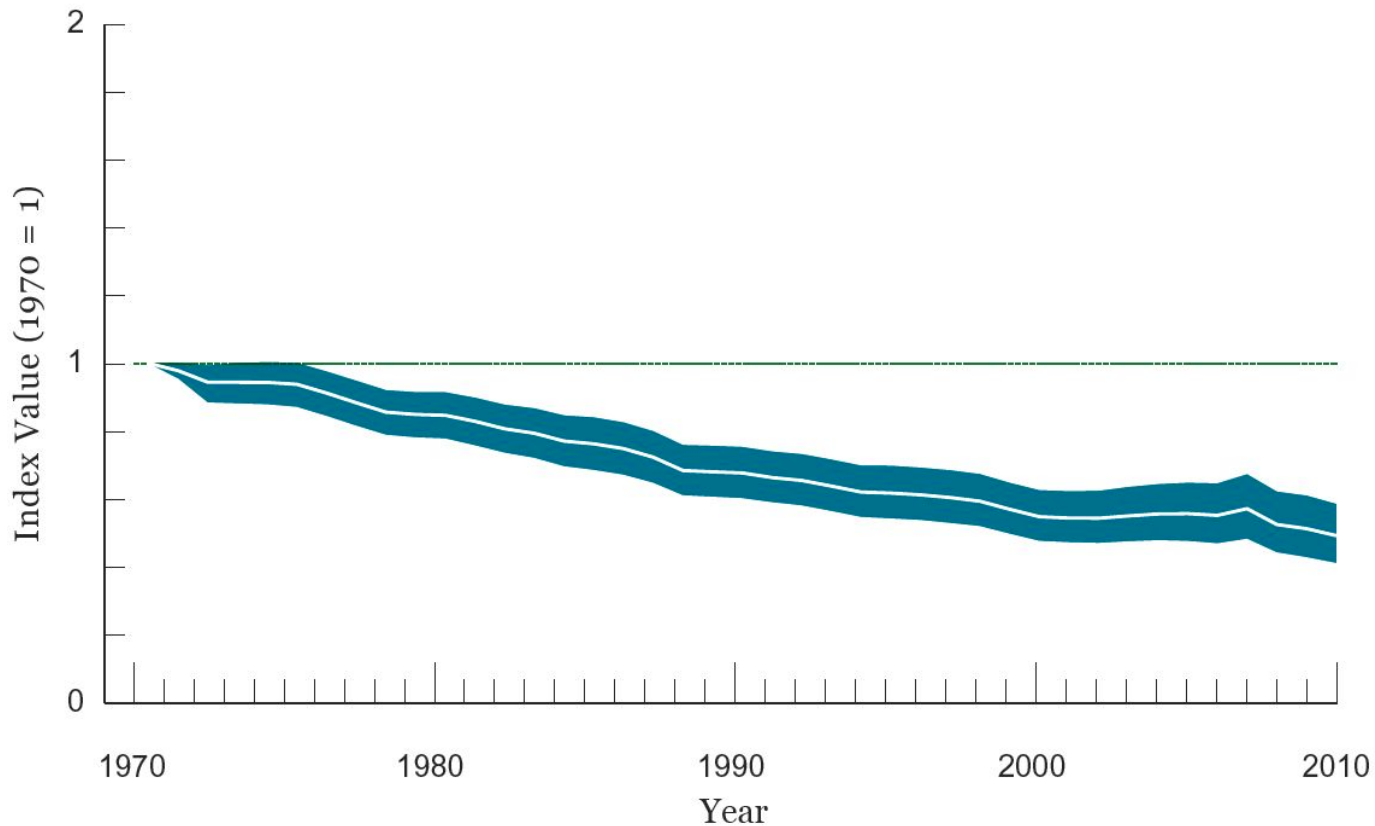
Figure 4: The global Living Planet Index shows a decline of 52 per cent between 1970 and 2010.
This suggests that, on average, vertebrate species populations are about half the size they were 40 years ago. This is based on trends in 10,380 populations of 3,038 mammal, bird, reptile, amphibian and fish species. The white line shows the index values and the shaded areas represent the 95 per cent confidence limits surrounding the trend. Image from McClellan et al. (2014).
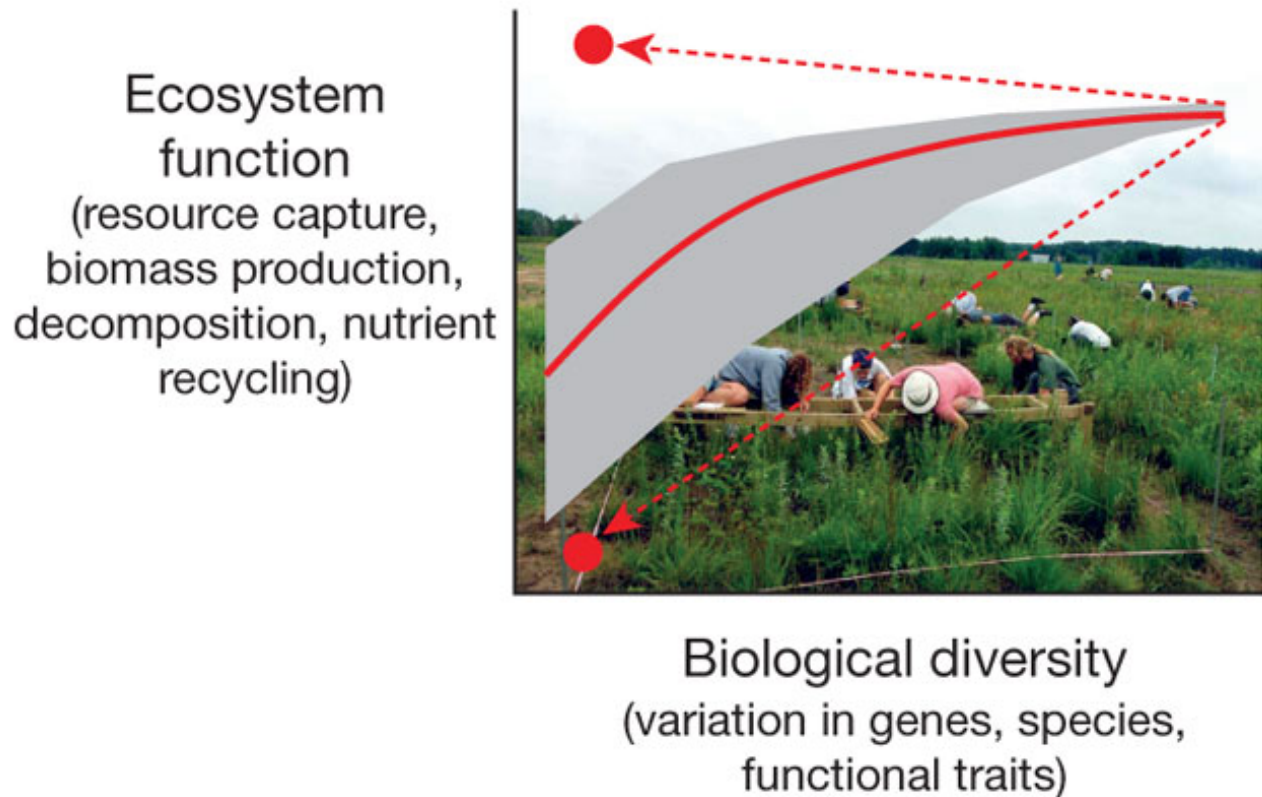
Figure 5: Consensus findings synthesized from hundred of biodiversity manipulation experiments show that biodiversity loss tends to degrade ecosystem functioning (red curve, grey shaded area represents 95% confidence intervals, red dots represent the maximum and minimum values of the most or least productive species grown alone in monocultures) and ecosystem stability (Cardinale et al., 2012). Remotely-sensed biodiversity observations are need to characterize these relationships at regional and global scales to address Objective 3. Image from Cardinale et al. (2012).
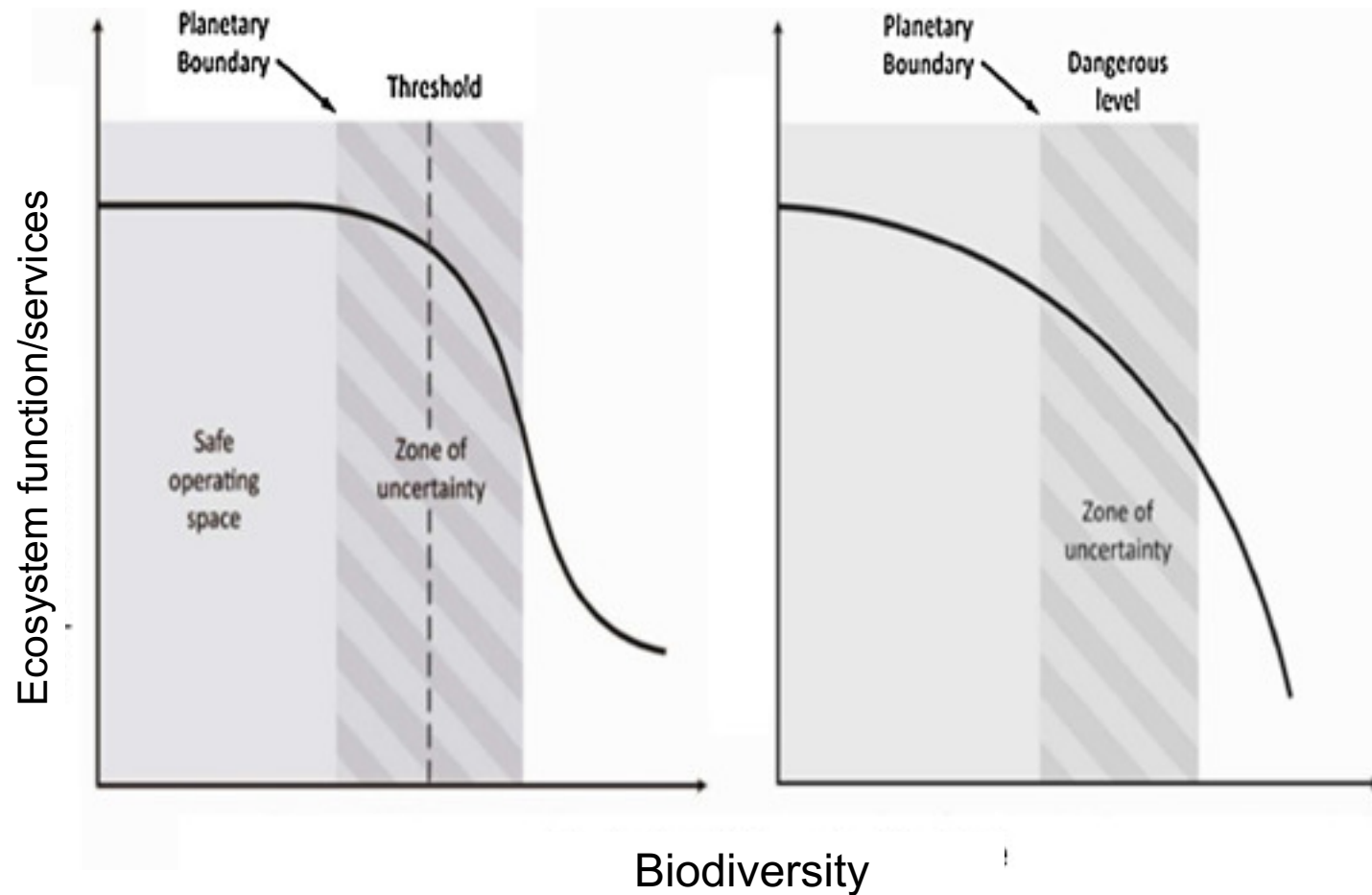
Figure 6: Global observations of biodiversity and ecosystem functioning are necessary to address Objective 4 to determine the future likelihood and potential consequences of of biodiversity change with an emphasis on identifying critical tipping points in Earth's life support systems. Adapted from Mace et al (2014) and Rockstrom et al (2009).
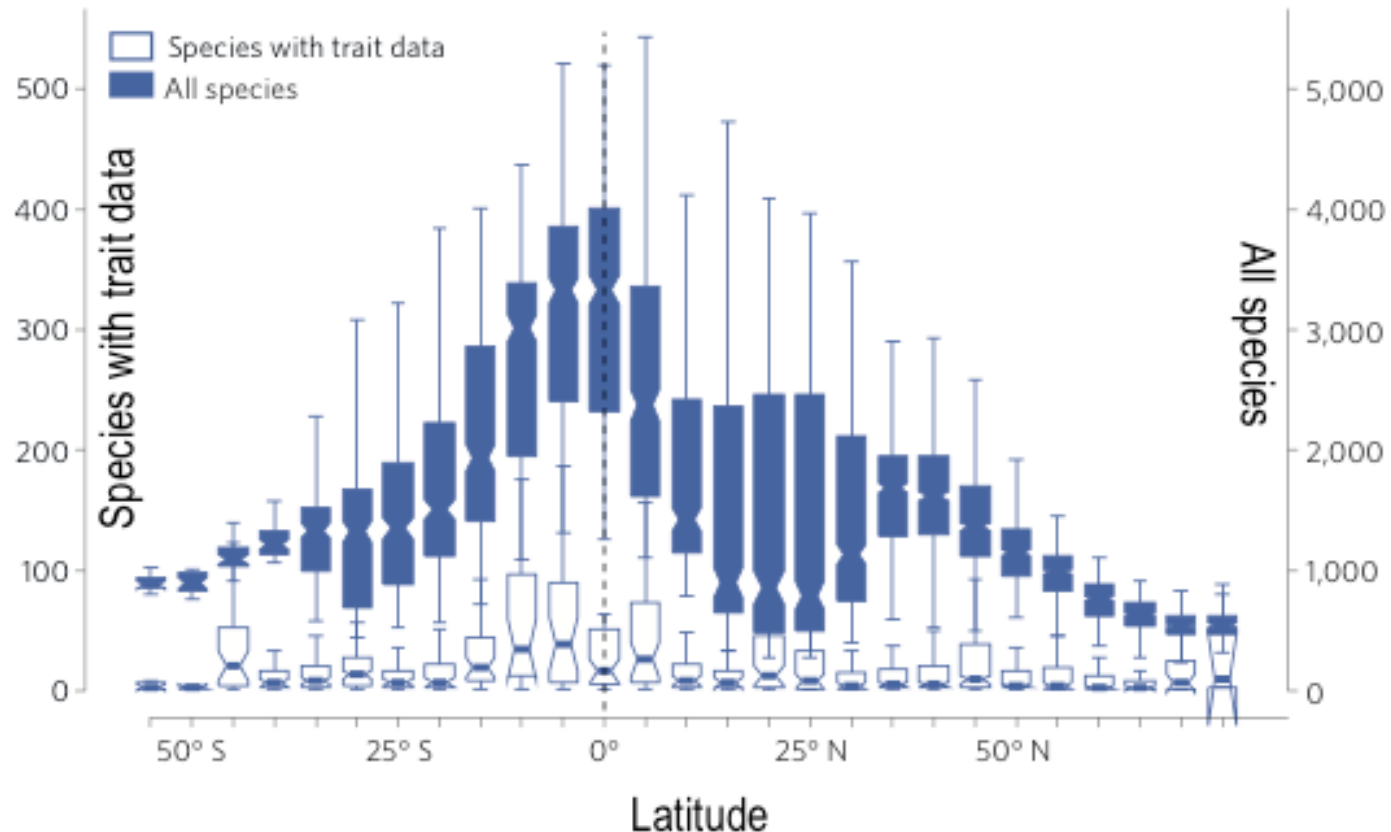
Figure 7: The data gap in regional trait measurements of terrestrial plant species (Jetz et al 2016). The graph shows the latitudinal variation in the number of vascular plant species for which at least one trait has been measured regionally (open boxes) in relation to all species expected for that region (filled boxes). Regions here are defined as 110x110 km grid cells (n=11,626); expected richness data is from Kreft and Jetz (2007) and regional trait data from the TRY plant trait database (accessed June 2015, Kattge et al 2011). Regions are analyzed at the grid cell level and their variations are summarized in 5 degree latitudinal bands. On average, *only 2% of species have any such regional measurements*, and the data gap is largest in the tropics. This limits our understanding of both biodiversity and ecosystem function and services.
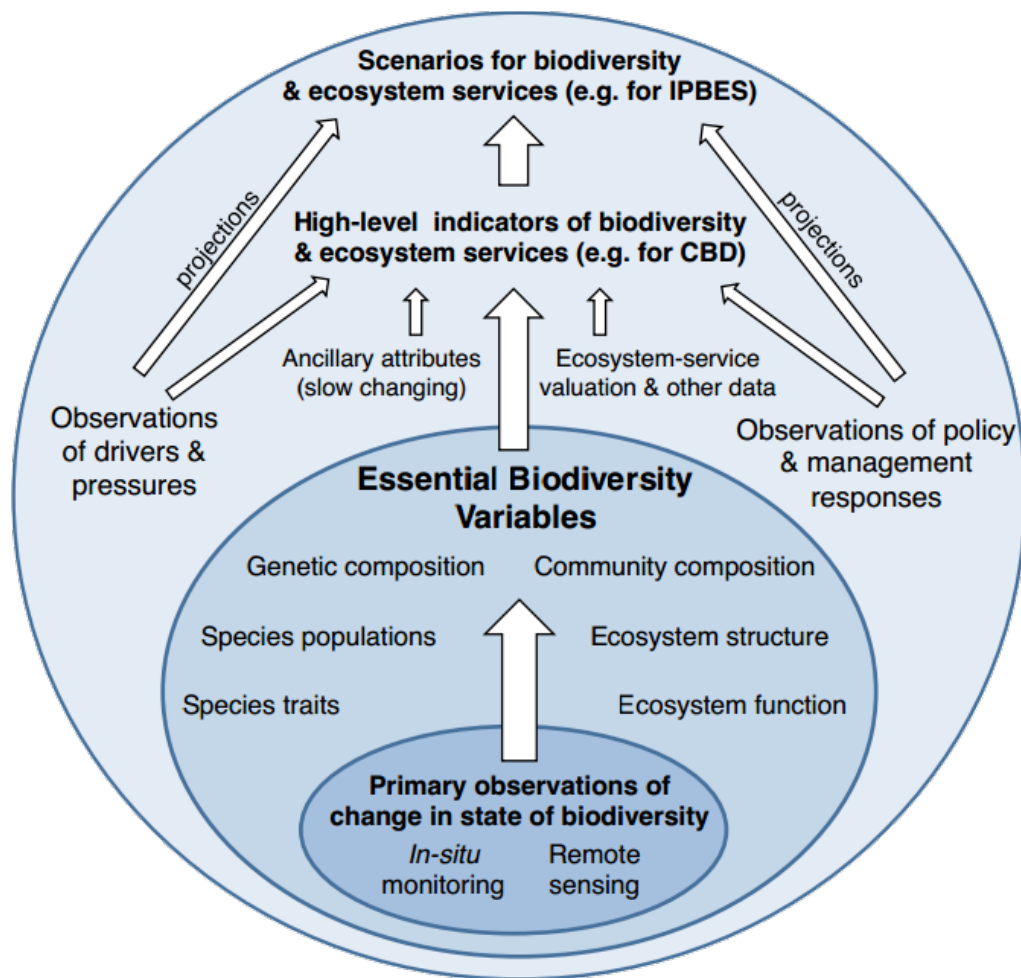
Figure 8: GEO BON is developing Essential Biodiversity Variables (EBVs), which are a minimum set of measurements to capture major dimensions of biodiversity change, complementary to one another and to other environmental change observation initiatives. EBVs cover the different dimensions of biodiversity change. They are temporally sensitive by having the ability to detect change. Most important, they are relevant, scalable, feasible and biological. Image from the GEO BON website (geobon.org).
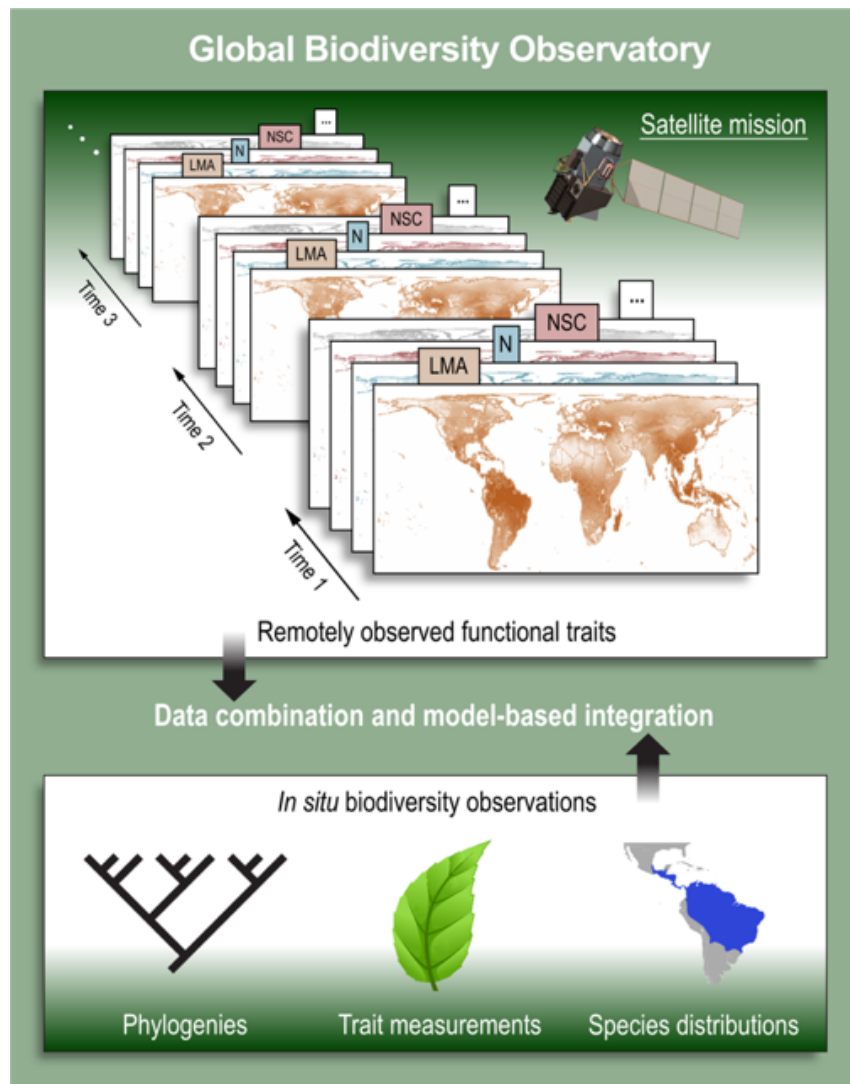
Figure 9: The Global Biodiversity Observatory envisioned by Jetz et al (2016) -- Space-based imaging spectrometer sensors capture global spatial data on key functional traits in time, including leaf mass per area (LMA), nitrogen (N), and non-structural carbohydrates (NSC) and others (Table 1). Other space-based sensors (such as LiDAR and radar) may also contribute measurements of other essential biodiversity variables (see RFI-2 response '3D Vegetation Structure and Dynamics' by Lavalle et al). An informatics infrastructure and appropriate modelling techniques connect this information with trait, evolutionary and spatial biodiversity information collected *in situ* worldwide at different spatial scales and levels of biological organization.
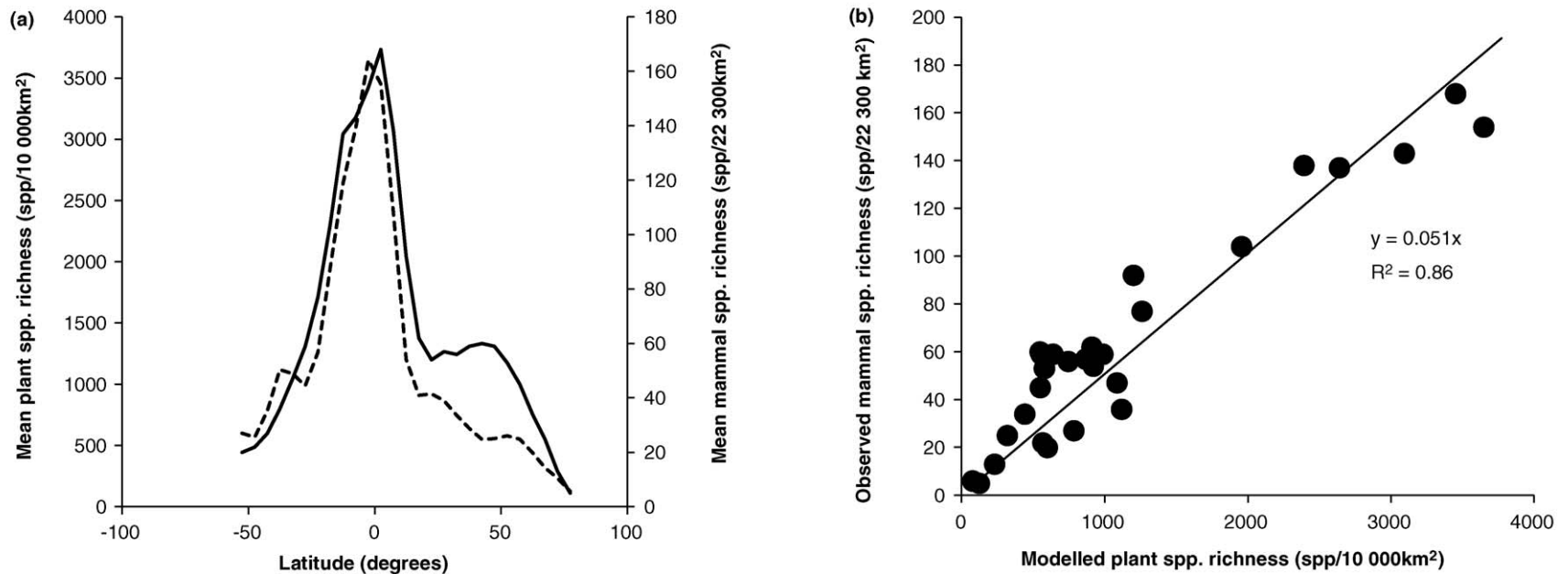
Figure 10: The spatial distribution of plant diversity is highly correlated with animal diversity. These two plots show the (left) latitudinal pattern of plant (dashed) and mammal (solid) species richness for 5 degree latitude bands and (right) the same relationship plotted as a regression. Images from Midgley et al 2010.
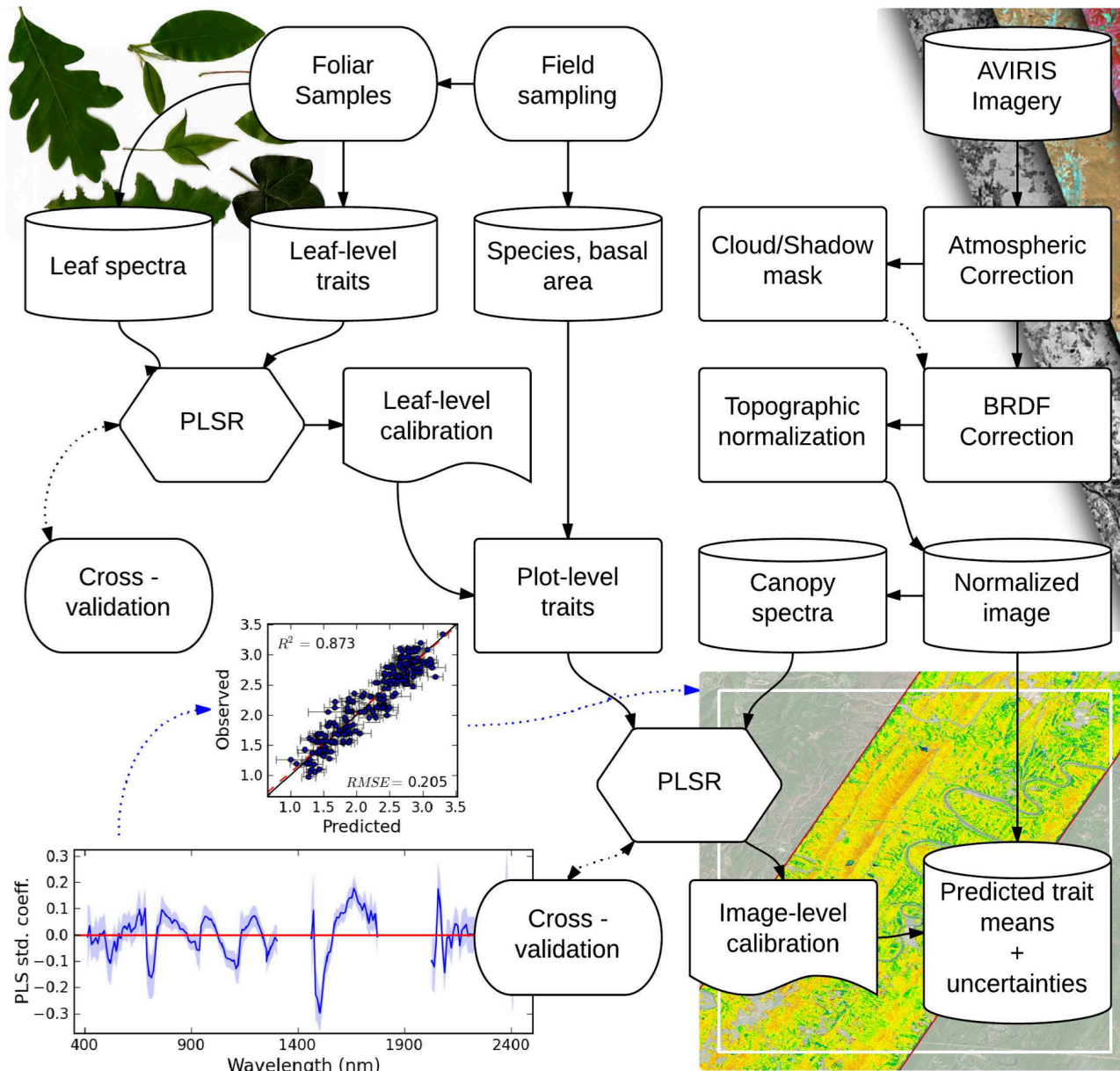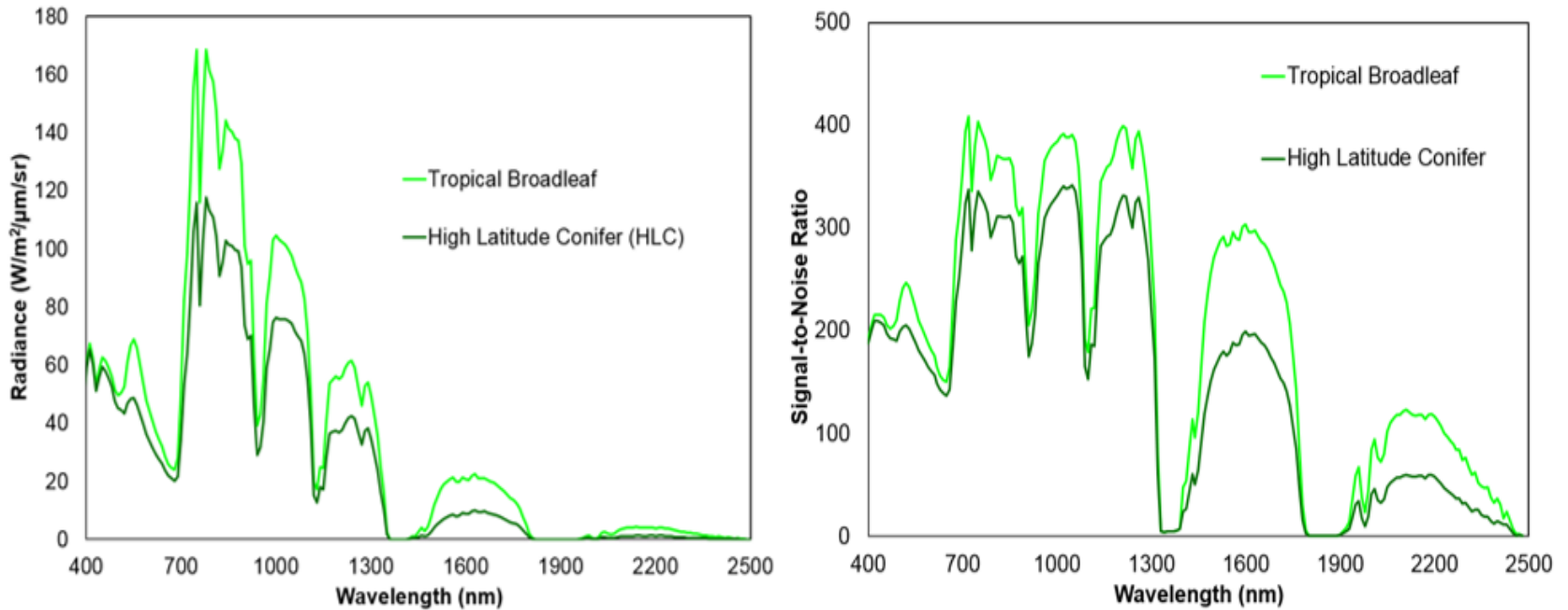
Figure 11: Conceptual diagram illustrating a mature plant trait retrieval algorithm, capable of retrieving many plant traits over multiple biomes using imaging spectroscopy (Singh et al 2015).

Figure 12: (left) Top of atmosphere radiance for a reference tropical broadleaf and a high latitude conifer. **(right)** Corresponding SNR that is consistent with the measurements by AVIRIS-C and other airborne imaging spectrometers that have been used to retrieve the plant traits of interest.
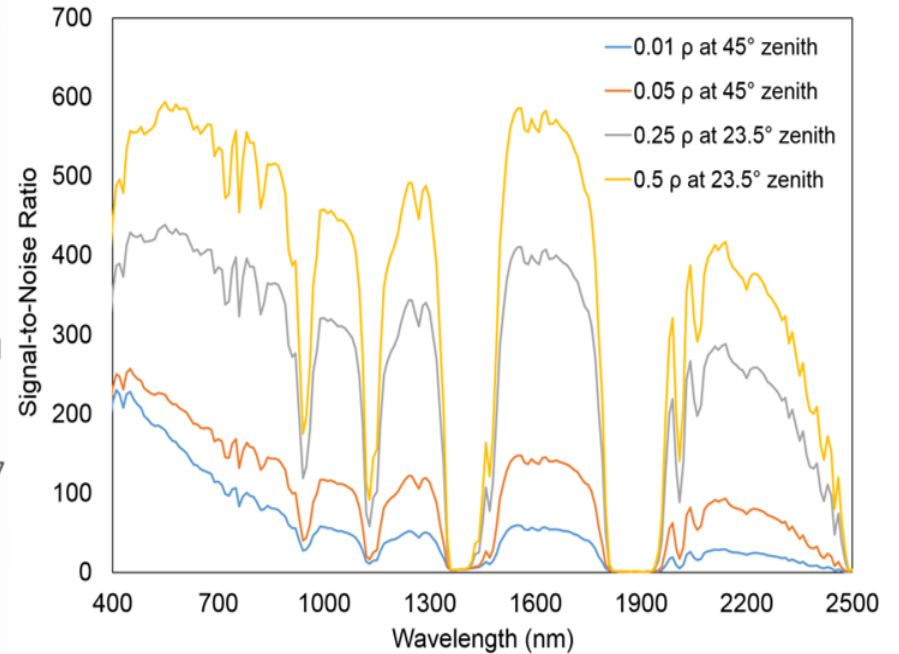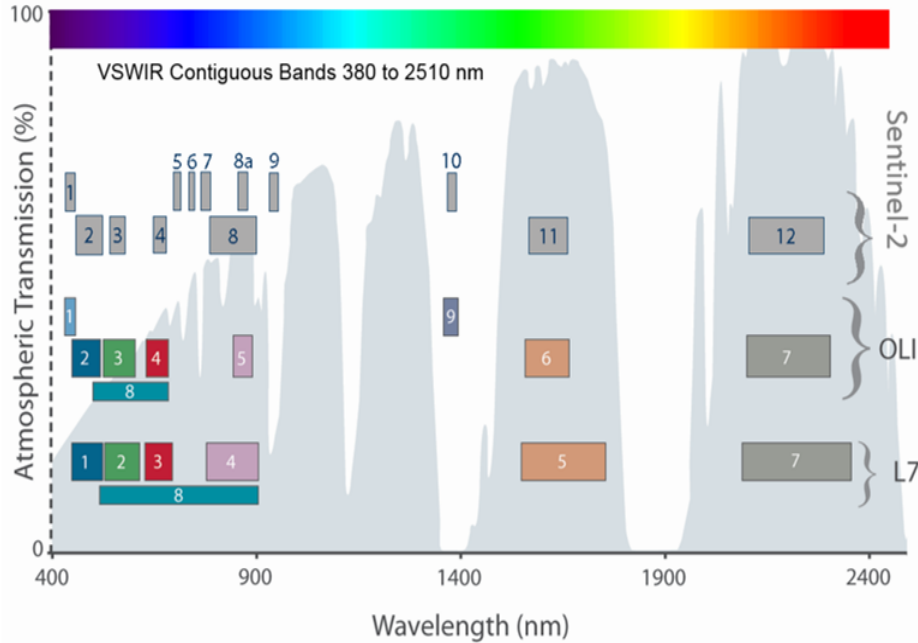
Figure 13: (left) Contiguous spectral coverage from 380 to 2510 nm of the F/1.8 VSWIR Dyson showing overlap with LandSat and Sentinal-2 bands. **(right)** Signal-to-noise ratio for 30 m sampling with F/1.8 VSWIR Dyson imaging spectrometer.
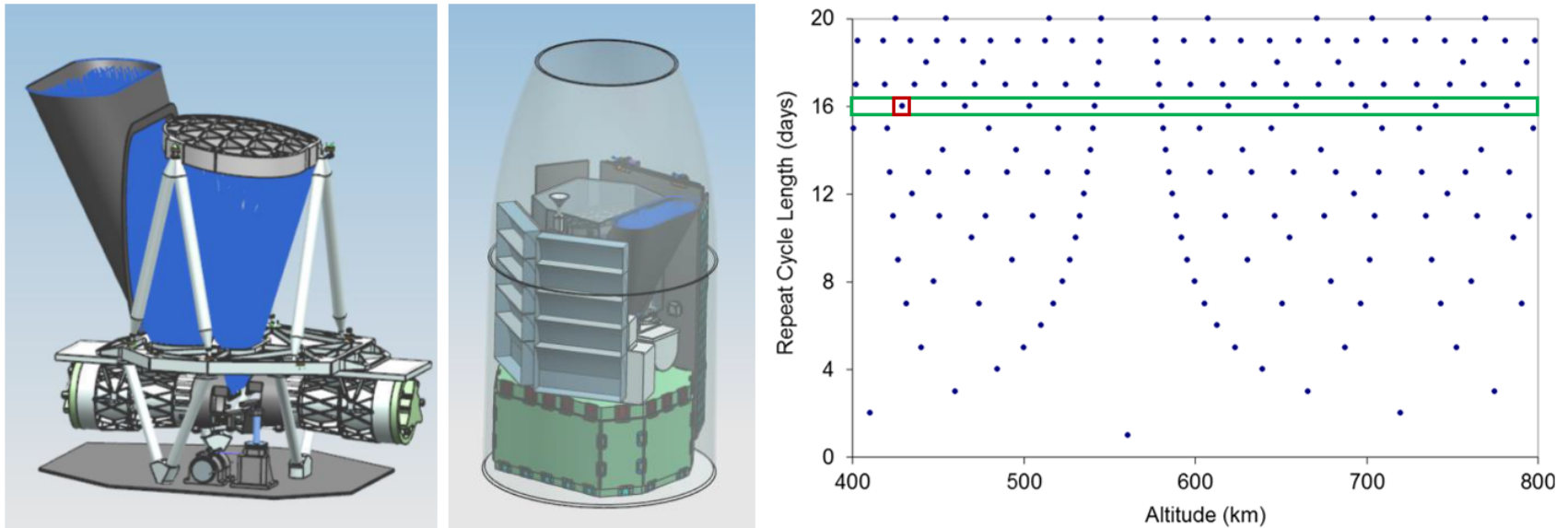
Figure 14: (left) Opto-mechanical configuration for a high SNR F/1.8 VSWIR imaging spectrometer system providing 185 km swath and 30 m sampling. **(center)** Imaging spectrometer with a spacecraft configured for launch in a Pegasus shroud for an orbit of 429 km altitude, 97.14 inclination to provide 16 day revisit for three years. **(right)** Orbital altitude and repeat options. An altitude of 429 km with a fueled spacecraft supports the three year mission with the affordable Pegasus launch. Higher orbits require a larger launch vehicle.
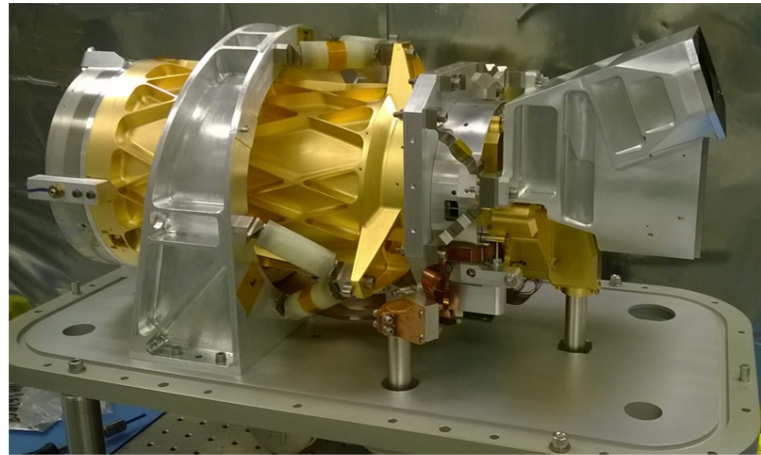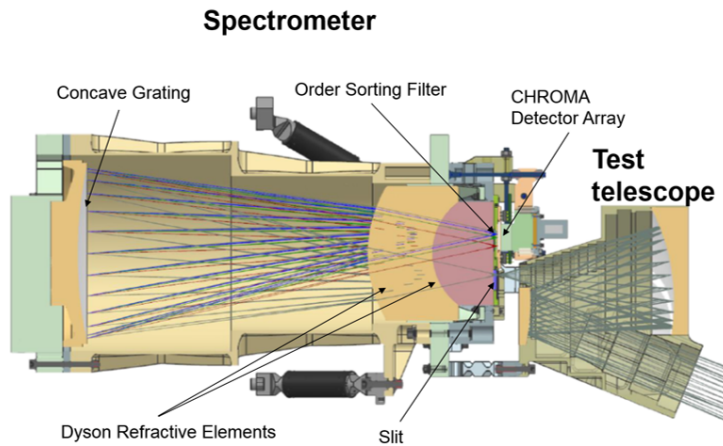
Figure 15: (left) Design of F/1.8 VSWIR Dyson covering the spectral range from 380 to 2510. **(right)** Developed, aligned and qualified Dyson with CHROMA full range VSWIR detector array.
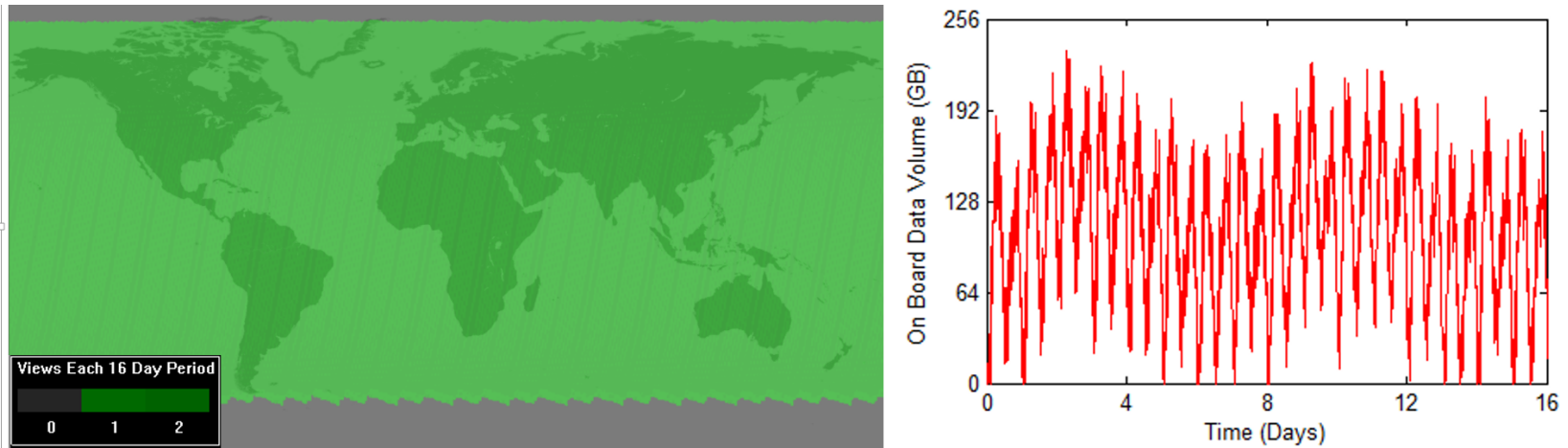
Figure 16: (left) Global illuminated surface coverage every 16 days. **(right)** On-board data storage usage for illuminated terrestrial/coastal regions with downlink using Ka Band to KSAT Svalbard and Troll stations. Oceans and ice sheets can be spatially averaged for downlink.

Table 1: List of key plant functional traits that can be estimated from imaging spectroscopy.

Functional characterization[1]	Trait	Example of functional role	Example Citations
Primary	Foliar N (% dry mass or area based)	Critical to primary metabolism (e.g., Rubisco),	Martin et al. 2008, Singh et al. 2015
	Foliar P (% dry mass)	DNA, ATP synthesis	Asner et al. 2015
	Sugar (% dry mass)	Carbon source	Asner & Martin 2015
	Starch (% dry mass)	Storage compound, carbon reserve	Matson et al. 1994
	Chlorophyll-total (ng g^{-1})	Light-harvesting capability	Zhang et al. 2008
	Carotenoids (ng g^{-1})	Light harvesting, antioxidants	Datt 1998
	Other pigments (e.g., anthocyanins; ng g^{-1})	Photoprotection, NPQ	van den Berg & Perkins 2005
	Water content (% fresh mass)	Plant water status	Gao 1996
Physical	Leaf mass per area (g m^{-2})	Measure of plant resource allocation strategies	Singh et al. 2015
	Fiber (% dry mass)	Structure	Singh et al. 2015
	Cellulose (% dry mass)	Structure	Singh et al. 2015
	Lignin (% dry mass)	Structure	Singh et al. 2015
Metabolism	Vcmax (μmol m^{-2} s^{-1})	Rubisco-limited photosynthetic capacity	Serbin et al. 2015
	Photochemical Reflectance Index (PRI)	Indicator of non-photochemical quenching (NPQ) and photosynthetic efficiency, xanthophyll cycle	Gamon et al. 1992; Asner et al. 2004
Secondary	Bulk phenolics (% dry mass)	Stress responses	Asner et al. 2015
	Tannins (% dry mass)	Defenses, nutrient cycling	Asner et al. 2015

[1]Categories of functional characterization are for organizational purposes only: *Primary* refers to compounds that are critical to photosynthetic metabolism; *physical* refers to non-metabolic attributes that are also important indicators of photosynthetic activity and plant resource allocation; *Metabolism* refers to measurements used to describe rate limits on photosynthesis; and *Secondary* refers compounds that are not directly related to plant growth, but indirectly related to plant function through associations with nutrient cycling, decomposition, community dynamics, and stress responses.

Algorithm	Data products	Where applied?	Citations	Estimated Maturity
Remote measurement of functional traits				
Townsend, Singh, and Serbin PLSR	LMA, N/N15, C, Chl, fiber, lignin, cellulose, tannins, phenolic glycosides, Vcmax	Upper Midwest (WI, MN, MI), Central and Northern Appalachians (MD, PA, WV, VA, NY), California	Singh et al. 2015; Serbin et al. 2015	TRL 5-6
Carnegie PLSR	LMA, leaf and canopy water, C, N, P, NSC, lignin, phenols, and multiple cations	Amazonian tropical forest; Mesoamerican tropical forest; Hawaiian tropical forests; North American temperate forests and shrublands	Asner et al. 2015	TRL 5-7
APEX	Chl Fluorescence, 1D radiative model inversion for Chl, LAI, pigments, leaf water	Various temperate forest ecosystems in Europe	Schaepman et al. 2015; Damm et al. 2015; Schweiger et al. 2015	TRL5
Spectral variation hypothesis				
Feret and Asner	Species alpha richness and beta compositional diversity	Amazonian tropical forest; Hawaiian tropical forest; California temperate forest and shrubland ecosystems	Feret and Asner 2015	TRL 4
Hërkul et al	Species alpha richness and Shannon index	Marine benthic ecosystem in Baltic Sea	Hërkul et al. 2013	TRL 4
Spectral classification and LiDAR ecosystem structure				
MESMA	Plant functional types and benthic cover types (e.g. coral, sand, algae)	Many terrestrial and marine benthic ecosystems (Atlantic, Pacific, Indian Oceans)	Dennison et al. 2003; Hochberg et al 2003; Goodman and Ustin 2007; Roth et al 2015	TRL 6
PHYDOTax	Chl-a (all taxa), Plankton functional types (diatoms, dinoflagellates, cyanobacteria)	Monterey Bay, Santa Barbara Channel	Palacios et al. 2015; Palacios et al. 2012.	TRL 5
3-D ecosystem structure	Vegetation vertical structure, landscape heterogeneity,	Many terrestrial ecosystems	Tang et al 2012; Montesano et al 2015; Tang et al 2016;	TRL 6-7

Table 2: Overview of biodiversity data algorithms for marine and terrestrial ecosystems and their maturities.